HOLISTIC APPROACH FOR CHARACTERIZING THE PERFORMANCE OF WIRELESS SENSOR NETWORKS

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ABSTRACT

Researchers are actively investigating wireless sensor networks (WSNs) with respect to node design, architecture, networking protocols, and processing algorithms. However, few researchers consider the impact of deployments on the performance of a system. As a result, an appropriate deployment simulator that estimates the performance of WSNs concerning several deployment variables is needed. This paper presents a holistic deployment framework that assists decision makers in making optimum WSN deployment choices by considering the terrain of their region of interest and type of deployment. This framework employs empirical propagation models to predict the performance of the deployment in terms of connectivity, coverage, lifetime, and throughput for stochastic and deterministic deployments in dense tree, tall grass, and short grass environments. The outlined framework can serve as a useful prototype for creating deployment simulators that optimize WSN deployments by considering terrain factors and type of deployment.

KEYWORDS

Wireless Sensor Networks, Stochastic Deployment, Deterministic Deployment & Terrain

1. INTRODUCTION

A wireless sensor network (WSN) is an information retrieval and processing platform with vast potential. The development of WSNs is a challenging field due to their many requirements and properties. Microsensors and related micromechanical processor systems embedded in each other have propelled recent advances in WSN development. These advances have precipitated the production of small, low-cost, distributed sensor devices for possessing, sensing, and signal processing in wireless communication. A WSN can be fitted with digital hardware devices that enable the creation of media content, such as cameras, microphones and other sensors. With the accompanying equipment, sensors can capture videos, images, audio, and scalar sensor data and then deliver the content through the network.

A WSN consists of several nodes that have sensing and self-networking capabilities. These nodes are connected in the WSN's wireless range to share information and transmit data to the base station. Collected data can assume numerous forms, such as, temperature, humidity, infrared radiation, images, audio, and videos. The base station obtains and receives data from sensors and processes the data for decision-making. Due to the diverse sensing capabilities of WSNs, they can be employed in military, industrial, healthcare, environmental applications[1]. For specialized

Natarajan Meghanathan et al. (Eds) : DaKM, SIPP, CCSIT, NCWMC - 2018
pp. 135–153, 2018. © CS & IT-CSCP 2018 DOI : 10.5121/csit.2018.81510

applications, unique categories of WSNs exist, such as wireless multimedia sensor networks (WMSNs), underwater wireless sensor networks, and wireless body sensor networks.

A WSN's deployment model is responsible for determining a node's position, size, cost, and layout over a region of interest (RoI). Deployment parameters have a direct influence on the WSN's performance and require optimization to achieve the application goal. Deploying WSN nodes is performed by one of two types of methods: stochastic methods or deterministic methods. Stochastic deployment is a practical deployment for large-scale networks, in which the nodes are randomly deployed. This approach is suitable for areas where access is difficult and placement of the nodes cannot be controlled. Nodes are usually dropped from an airplane or other airborne mechanism, which produces a uniform distribution of nodes. The second choice is to deterministically deploy sensor nodes, which can be the best choice for achieving the system goals. In deterministic deployment, sensor node positions are predetermined, and an accessible region of interest exists to place sensor nodes[2].

WSN performance analysis currently assumes flat environments and provides unrealistic results[3]. In real-life situations, sensor nodes are deployed in environments that contain various obstacles, such as trees, grass, and concrete. Due to variations in application requirements, nodes can be placed at different heights, which may cause changes in propagation paths that differ from those in the traditional free space propagation model. Using empirical propagation models, this research aims to study the effects of the deployment environment on WSN performance. Empirical propagation models of tall grass, short grass, and dense trees are used to estimate deployment coverage, connectivity, network lifetime and throughput[4].

This paper presents a realistic decision-making methodology for stochastic and deterministic deployments of WSN. The remainder of the paper is organized as follows: In Section 2, a literature review is presented. A modeling and simulation approach using empirical radio models and stochastic and deterministic deployments is presented in Section 3. Section 4 shows the simulation results for theoretical and realistic scenarios. Section 5 presents the study's conclusions and a discussion of future research.

2. BACKGROUND WORK

The author in [5] provides a framework and/or detailed process for creating simulators for application-specific WSN deployments. This simulator helps decision-makers select alternatives for WSN deployments. This framework considers application-specific factors and may be utilized in WSN stochastic deployment optimizations. The results indicate that the simulation offers a full view of every deployed node. The simulation also shows the influence of various deployment parameter levels on the efficiency of a deployment. Although the framework presented by the study offers guidance to the processes for building deployment simulators, the researchers note the need for improvement in various aspects. First, improvement in deployment distributions is needed; this problem is central to any WSN stochastic deployment. Another suggested aspect for improvement in the study pertains to RF models. The study indicates that accurate RF propagation modeling is a highly important WSN deployment topic. RF models prevent the generation of misleading conclusions. Every deployment simulator should require access to these models to improve the accuracy of their results.

The author in [6] investigated a deterministic and random node deployment, particularly for large-scale wireless sensor networks. This study examined three main performance metrics: energy consumption, message transfer delay, and coverage. The research considered three competing node deployment schemes: uniform random scheme, square grid scheme, and pattern-based Tri-Hexagon Tiling (THT) scheme. The study employed a simple energy model that examined energy consumption for every deployment scheme. The researchers concluded that a WSN can rely on THT as the best performing node deployment strategy. In terms of future research, the study recommends the consideration of other deployments and a more detailed WSN energy model.

In another study [7], the researchers performed simulations of random node deployments over a square area of varying densities and assumed that their network was composed of simple sensor nodes. The research also proposes a model for simulating a random sensor deployment and other features to empirically calculate the connectivity probability between a certain number of anchor and sensor nodes. The study proposes that future studies should concentrate on implementing an accurate RF propagation model to prevent misleading conclusions from simulated results.

The study [8] proposes a systematic methodology for sensor placement using random distributions. The quality of a deployment is evaluated based on a proposed set of measures. The study thoroughly examines the impact of deployment strategies on WSN performance. The study also proposes a novel hybrid deployment scheme using the suggested deployment quality measures that attain the best performance. The deployment scheme and measures of deployment quality are evaluated using extensive simulations. The results indicate that the hybrid strategy outperformed other deployment schemes, including random, exponential, Gaussian, and uniform distributions. This strategy outperformed other strategies for grounds of delay, packet delivery ratio, network partition time, coverage, and average residual energy. This research aims to derive accurate analytical models to compare with simulation results.

A further study [9] emphasizes two important aspects of WSN planning and/or deployment platforms. The framework is based on the J-Sim simulator, which details the manner in which a platform can be implemented. The platform aims to identify application-specific requirements, simulate an entire WSN, and obtain a deployment solution that is optimal in terms of node numbers, node type, node placement method, and various protocols. The researchers plan to reinforce a WSN planning and deployment performance evaluation and/or optimization in future studies. Additional novel models and/or protocols need to be investigated, including route protocols, obstacle, radio, and environment models.

The study in [10] includes a research-in-progress that aimed to develop a decision-support system that can be used to predict optimal WSN node deployments for a given area. This proposed system includes simulation, image-processing, decision-making and prediction capabilities without the use of extensive parametric statistical techniques. The proposed system would enable rapid, optimized, cost-effective, and reliable sensor deployment on various existing structures and/or terrains during natural disasters and extreme scenarios, such as military operations. Considering that the system would be designed using open architecture and freely offered to the entire research community, it will likely impact future WSN research. This effect would fill unmet decision-support system demand and aid in designing and managing complex WSN deployments.

Another paper [11] discusses various node deployment schemes, including efficiency enhancing parameters. The study proposes a new deployment scheme, in which the area of interest is divided into different small circles with nodes that are positioned at the center and diametric ends. This particular pattern has two-coverages (similar to hexagonal and square schemes) and has a degree of four. Based on the simulation results, the proposed pattern utilizes fewer nodes. The scheme offers a better degree and coverage than triangular, squared and hexagonal schemes. The scheme efficiently conserves energy with minimum delays compared with other schemes. However, this research does not consider the impact of terrains and obstacles.

In additional research [12], the author contributed to identifying methods for prolonging the network lifetime. To evaluate the lifetime of sensor networks, the best approach for placing sensors with the highest efficiency is required. Using MATLAB software for simulation, the authors developed a network that consists of nodes that are geometrically distributed in the form of stars. Each star deployment had a different number of branches with different existent energy. Based on the simulation analysis, these researchers discovered that geometric distributions provide a significant increase in WSN lifetimes compared with random distributions.

Researchers have conducted a survey [13] aimed at discovering the most efficient deployment of sensor networks, which usually have unbalanced energy consumption. This research evaluated the impact of Gaussian deployments on the performance of a wireless sensor network. The authors performed simulations on the following elements: random traffic, homogeneous nodes, and stationary sinks. This procedure included uniform and Gaussian deployment strategies. These two strategies were divided into random and engineered deployments. To ensure a comprehensive analysis of the given area, future research should examine the performance of other deployment strategies.

The author of [14] focused on evaluating the appropriate number of clusters that can be used in a WSN with the goal of maximizing its lifetime. Their research contributed to the evaluation of the hierarchical clustering routing protocol. The authors focused on applying this protocol to several deterministic deployment schemes, such as uniform, star, hexagonal and circular distribution. The analysis of the simulation results revealed a significant relationship between the sink location and the number of clusters, which maximizes the WSN lifetime. Thus, a higher number of clusters is useful for a sink that is located in the center of a sensor area, whereas a smaller number of clusters is useful for a sink that is located far from the sensor area. These distributions reduce the energy consumed by the WSN. This research uses theoretical propagation models that do not consider the effect of terrains on WSN performance.

The study in [15] calculates the efficiency of different deployment patterns. These patterns were compared in terms of two performance measures. The first performance measure is the network efficient coverage area ratio; the second performance measure is the total coverage area for varying number of nodes. The research in this paper is based on exploring the best approach to deploying wireless sensor nodes that ensures the highest efficiency in coverage areas using efficient coverage area ratios. Using MATLAB as a simulation tool, they conducted a simulation based on the deploying sensor nodes in two patterns: square and triangular. The analysis shows that the triangle sensor node deployment pattern is more efficient in minimizing the number of nodes, efficiency, and energy consumption.

A thorough review of the literature reveals a lack of studies that evaluate WSN deployment performance using practical methods. An extensive range of assessment approaches exist; however, the majority of these approaches use conventional linear measurements, which are not applicable to WSN. Instead, propagation models are commonly employed to test in-field or simulate the performance in different environments and terrains. Propagation models seem to expose the most critical gaps in the design and methodology of WSNs, including routing protocol, measured performance, and matters related to the continuous use of the technology. Assessments performed with this model exhibit drastic differences in WSN performance in various environments. Terrain, its density, and other environmental constraints occur to vary the effectiveness of a WSN even though the sensor capacity was reviewed as a complex of evolving signals. Using empirical propagation models is increasingly becoming a vital factor in simulating WSNs to predict the performance of real deployments. Applying free space propagation models is considered to be an overly optimistic prediction method that simplifies the difficulty of deployment. The Office of Naval Research (ONR) [16] claims that “modeling environments capable of optimizing the placement of available sensors within an area of interest to achieve persistent surveillance". A demand exists to optimize WSN deployment frameworks by including empirical propagation model's deployment choices via the inclusion of several factors, such as terrain-driven deployment, connectivity, coverage, lifetime, and throughput in one holistic system [17].

3. REALISTIC WSN SIMULATION

This section presents the components of the WSN deployment framework. Simulation experiments are performed on a MATLAB platform to implement the network and compare the performance. The framework supports stochastic and deterministic deployments, different theoretical and empirical propagation models, variable transmit power, and variable sensing ranges.

3.1. Empirical Propagation Model

A propagation model is used to test in-field or simulate the performance of a WSN in different environments and terrains. Propagation models seem to expose the most critical gaps in the design and methodology of WSNs, including routing protocol, measured performance, and matters related to the continuous use of the technology. To obtain a realistic performance analysis of the deployment, empirical propagation models are utilized to calculate several performance metrics. In this framework, six different propagation models that cover various types of terrains are employed. Each terrain propagation model was measured with different heights[4]. This research investigates three types of terrains: short grass, tall grass, and dense trees with different heights. Table 1 shows the propagation models.

Table 1. Empirical Propagation Model.

Terrains	**Cases**	**Models**
Short Grass	Nodes at zero height	$70.62+34.01\log_{10}d$
	Nodes at 17 cm	$53.29+39.00\log_{10}d$
Tall Grass	Nodes at 3 cm	$53.29+31.31\log_{10}d$
	Nodes at 50 cm	$37.02+35.33\log_{10}d$
Dense Tree	Nodes at zero height	$52.23+28.11\log_{10}d$
	Nodes at 50 cm	$35.0+32.74\log_{10}d$

3.2. Network Deployment

The framework supports stochastic and deterministic deployment[2]. For stochastic deployments, the positions of the nodes are randomly determined over the defined area. In addition, the framework supports three deterministic deployments: triangular, hexagonal and square deployments as shown in Fig. 1. For these deployments, the position of each node is defined based on the type of deployment, the area size and the distance between two nodes.

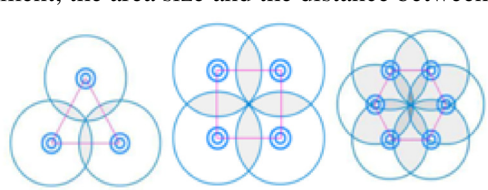

Figure 1. Deterministic deployments: triangular, square and hexagonal.

3.3. Empirical Energy Models

The energy dissipation of a WSN can be estimated by calculating the cost of the routing communication activity. The LEACH protocol [18], which focuses on fairly distributing the energy node between two WSN nodes, is employed to maximize the network lifetime and the energy dissipation on each node. The main idea of the LEACH is clustering, in which the network is divided into clusters that have a cluster head and members. The number of single hop communications that directly connect to the base station is lessened by only enabling the cluster heads to communicate. The cluster head aggregates the data from the cluster member and directly sends it to the base station. To measure the performance of the LEACH, the radio energy model [19] [20] is used to estimate the energy dissipation for transmitting and receiving data, as shown in Fig.2. The transmitter consumes energy due to power amplification and radio electronics, whereas the receiver loses energy due to radio electronics. To calculate the power attenuation between the sender and the receiver, the distance between them is employed. The propagation loss for each type of terrain is inversely proportional, as shown in Table I.

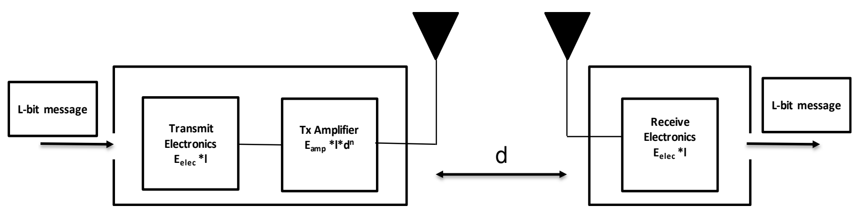

Figure 2. Energy model in wireless sensor network.

The radio energy dissipation to transmit a message that has l-bit over a distance d will be:

$$E_{Tx}(l,d)=E_{Tx\text{-}elec}(l)+E_{Tx\text{-}amp}(l,d) \tag{1}$$

Empirical models follow a first-order log-distance polynomial model, and the equations that express the relationship among the path loss, transmitted power and received power is:

$$Lp=Pt[dBm]-Pr[dBm]+Gt[dB]+Gr[dB] \tag{2}$$

Where:

Lp: the path loss in dB; Pt: the transmitted power; Pr: the received power; Gt: the transmitter gain; Gr: the receiver gain.

The transmit power can be adjusted depending on the design and needs of a WSN. To obtain the transmit power, each terrain path loss model and equation (2) are combined:

$$P_{r\_short\_grass\_node\_at\_0m}=\frac{Pt\ Gt\ Gr}{11.534532\times 10^{6}\times d^{3.401}} \tag{3}$$

$$P_{r\_short\_grass\_node\_at\_17cm}=\frac{Pt\ Gt\ Gr}{0.00685488\times 10^{6}\times d^{3.9}} \tag{4}$$

$$P_{r\_tall\_grass\_node\_at\_3cm}=\frac{Pt\ Gt\ Gr}{0.2133\times 10^{6}\times d^{3.131}} \tag{5}$$

$$P_{r\_tall\_grass\_node\_at\_50cm}=\frac{Pt\ Gt\ Gr}{0.005035\times 10^{6}\times d^{3.533}} \tag{6}$$

$$P_{r\_dense\_tree\_node\_at\_0m} = \frac{\text{Pt Gt Gr}}{0.167 \times 10^6 \times d^{2.811}} \tag{7}$$

$$P_{r\_dense\_tree\_node\_at\_0m} = \frac{\text{Pt Gt Gr}}{3.162 \times 10^6 \times d^{3.274}} \tag{8}$$

The amplifying energy on the transmitter side depends on two factors: receiver sensitivity and noise figure. To obtain the minimum transmitted power, a backward process is performed starting from the power threshold to ensure that the received power must be higher than the threshold. Multiplying the bit rate by the transmit energy per bit will generate transmit power and by inputting the value of amplifying energy for each type of terrain:

$$Pt = \begin{cases} E_{\text{short\_grass\_0\_amp}} R_b d^{3.401} \\ E_{\text{short\_grass\_17\_amp}} R_b d^{3.9} \\ E_{tall\text{\_grass\_3\_amp}} R_b d^{3.131} \\ E_{tall\text{\_grass\_50\_amp}} R_b d^{3.53} \\ E_{dense\text{\_tree\_0\_amp}} R_b d^{2.81} \\ E_{dense\text{\_tree\_50\_amp}} R_b d^{3.274} \end{cases} \tag{9}$$

The received power can be obtained using the empirical channel propagation models from the previous section:

$$\Pr = \begin{cases} \dfrac{E_{\text{short\_grass\_0\_amp}} R_b G_t G_r}{11.535 \times 10^6} \\ \dfrac{E_{\text{short\_grass\_17\_amp}} R_b G_t G_r}{0.0069 \times 10^6} \\ \dfrac{E_{tall\text{\_grass\_3\_amp}} R_b G_t G_r}{0.2133 \times 10^6} \\ \dfrac{E_{tall\text{\_grass\_50\_amp}} R_b G_t G_r}{0.005 \times 10^6} \\ \dfrac{E_{dense\text{\_tree\_0\_amp}} R_b G_t G_r}{0.167 \times 10^6} \\ \dfrac{E_{dense\text{\_tree\_50\_amp}} R_b G_t G_r}{3.162 \times 10^6} \end{cases} \tag{10}$$

The received power can be obtained using the empirical channel propagation models from the previous section:

$$E_{\text{short\_grass\_0\_amp}} = \frac{P_{r-thresh} \times 11.535 \times 10^6}{R_b \times G_t \times G_r} \tag{11}$$

$$E_{\text{short\_grass\_17\_amp}} = \frac{P_{r-thresh} \times 0.0069 \times 10^6}{R_b \times G_t \times G_r} \tag{12}$$

$$E_{tall\text{\_grass\_3\_amp}} = \frac{P_{r-thresh} \times 0.2133 \times 10^6}{R_b \times G_t \times G_r} \tag{13}$$

$$E_{tall\text{\_grass\_50\_amp}} = \frac{P_{r-thresh} \times 0.005 \times 10^6}{R_b \times G_t \times G_r} \tag{14}$$

$$E_{dense\_tree\_0\_amp} = \frac{P_{r-thresh} \times 0.167 \times 10^6}{R_b \times G_t \times G_r} \quad (15)$$

$$E_{dense\_tree\_50\_amp} = \frac{P_{r-thresh} \times 3.162 \times 10^6}{R_b \times G_t \times G_r} \quad (16)$$

The following formula is used to calculate the receiver threshold:

$$P_{r\text{-}thresh}[dBm] = 10\log(KTB) + F[dB] + C/N[dB] \quad (17)$$

where:

K: Boltzmann's constant; T: Absolute temperature in Kelvins; KT≈ 4*10-18 mW/Hz; B: Bandwidth of the signal in Hz; F: Noise figure of the receiver; C/N: Signal-to-noise ratio.

To successfully receive a packet, the received power must be higher than -94 dBm. The dissipated energy for each bit in the transceiver electronics is set to 50 nJ/bit. By adding the values in this experiment (Gt=Gr=1.86 dB, ht=hr=5 cm, Rb=1 Mbps), the amplifying energy for each type of terrain would be:

$$E_{short\_grass\_0\_amp} = 1.949 \text{pJ/bit/ m}^{3.401} \quad (18)$$

$$E_{short\_grass\_17\_amp} = 1.158 \text{pJ/bit/ m}^{3.9} \quad (19)$$

$$E_{tall\_grass\_3\_amp} = 0.036 \text{pJ/bit/ m}^{3.131} \quad (20)$$

$$E_{tall\_grass\_50\_amp} = 0.851 \text{fJ/bit/ m}^{3.533} \quad (21)$$

$$E_{dense\_tree\_0\_amp} = 0.0282 \text{pJ/bit/ m}^{2.811} \quad (22)$$

$$E_{dense\_tree\_50\_amp} = 0.5344 \text{pJ/bit/ m}^{3.27} \quad (23)$$

A comparison with well-known theoretical propagation models was performed to show the effect of real environment terrains on a WSN. The impact of free space and two-ray propagation models on WSN performance are compared with the performance of all empirical models. This effect drives the energy models, and using the parameters in this experiment, the energy models would be:

$$E_{free\_space\_amp} = 1.10 \text{fJ/bit/ m}^{2} \quad (24)$$

$$E_{two\text{-}ray\_amp} = 0.0013 \text{pJ/bit/ m}^{4} \quad (25)$$

3.4. Node Connectivity

The connectivity of a network measures how well the nodes in a network are connected within the deployed area. The connection between two wireless nodes comprise either a direct link or an indirect link. To define a communication link between two nodes $n_1(x_1,y_1)$ and n_2 (x_2,y_2), the Euclidean distance d between them is calculated.

$$d(n_1,n_2) = \sqrt{(x_1 - x_2)^2 + (y_2 - y_1)^2} \quad (26)$$

If the Euclidean distance between the two nodes is less than the communication range, it is defined as a directly connected node. For these nodes, the maximum transmission range determined by the empirical RF propagation model of a specific environment will determine the connectivity between these nodes.

$$d_{short\_grass\_node\_at\_0m} = \left(\frac{P_t G_t G_r}{11.534532 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{3.401}} \tag{27}$$

$$d_{short\_grass\_node\_at\_17cm} = \left(\frac{P_t G_t G_r}{0.00685488 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{3.9}} \tag{28}$$

$$d_{tall\_grass\_node\_at\_3cm} = \left(\frac{P_t G_t G_r}{0.2133 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{3.131}} \tag{29}$$

$$d_{tall\_grass\_node\_at\_50cm} = \left(\frac{P_t G_t G_r}{0.005035 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{3.533}} \tag{30}$$

$$d_{dense\_tree\_node\_at\_0m} = \left(\frac{P_t G_t G_r}{0.167 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{2.811}} \tag{31}$$

$$d_{dense\_tree\_node\_at\_50cm} = \left(\frac{P_t G_t G_r}{11.534532 \times 10^6 \times \mathrm{P}_{\mathrm{r}-thresh}}\right)^{\frac{1}{3.274}} \tag{32}$$

The connectivity matrix is used to evaluate an entire network's connectivity. The matrix has the size of n * n, where n is the number of nodes in the network. Based on the radio range and the distance between the nodes, the matrix element will have a value of 1 if they are connected and a value of 0 if they are not connected. The indirect links between the nodes are calculated by scanning all nodes to identify indirect nodes between the previous two nodes. The connectivity percentage is calculated when the connectivity matrix is ready. The framework checks the connectivity among all nodes on each LEACH round and shows the variation in the connectivity for the surviving nodes.

3.5. Region of Interest Coverage

Coverage is one of the most important metrics that measures the deployment effectiveness and the quality of service of a WSN. Coverage indicates the number of points in the deployment area that are covered by the deployed sensors. The binary disc sensing model is adapted to compute the average. The sensing area is the circle that surrounds a sensor with the radius r, which is equal to the sensing range of the sensor. Each point that does not fall within this radius is considered to be an uncovered point. The sensing range is assumed to be the same for each sensor and can be determined as an input.

$$C_{xy}(S_i) = \begin{cases} 1 : if\, d(S_i, P) \le r \\ 0 : otherwise \end{cases} \tag{33}$$

where Si is the sensor node position, P is the position of any node in the area, and r is the sensing range. The distance between the node and the point is calculated using the Euclidean distance equation. The percentage of coverage is given by:

$$Coverage = \frac{c}{\sum_{p \in P} 1} \times 100 \tag{34}$$

The framework checks the change in coverage on each round due to the change in the remaining number of nodes.

4. DEPLOYMENT ANALYSIS

In this section, the holistic performance of stochastic and deterministic deployment is analyzed for all terrains. The provided results support decision-making processes by studying the impact of several factors that influence the WSN performance. MATLAB is used to implement and analyze the deployment. The following section shows the analysis of the simulation output, where the deployment area is a rectangle with a size of 200 m X 200 m. The base station is located at 100 m X 205 m. Four common deployments tested with the same variables were applied to all environments to estimate the coverage, connectivity, lifetime, and throughput. The data packet has 6400 bits, and the control packets have 200 bits. The number of cluster heads for each round is 5% of the total number of remaining nodes. The initial energy is the same for all nodes, which is 2 joules. The holistic performance of the network was tested with a variable number of nodes and sensing ranges.

4.1. Lifetime

Using the presented framework, the lifetime is computed and simulated, and the results are presented in Figures 3-6.

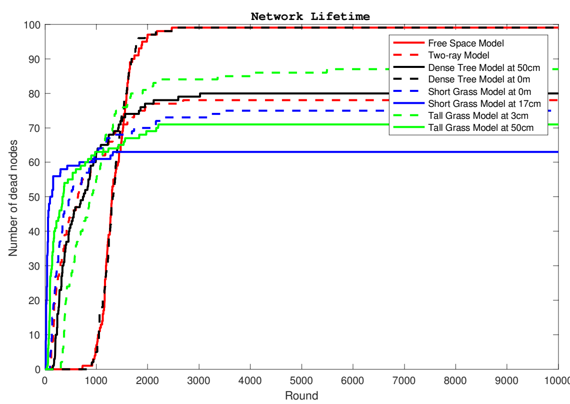

Figure 3. Lifetime of random deployment in rounds for all terrains.

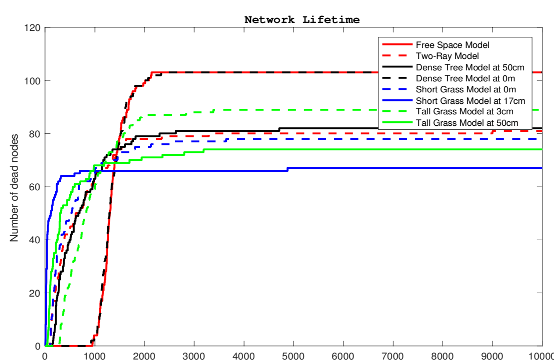

Figure 4. Lifetime of triangular deployment in rounds for all terrains.

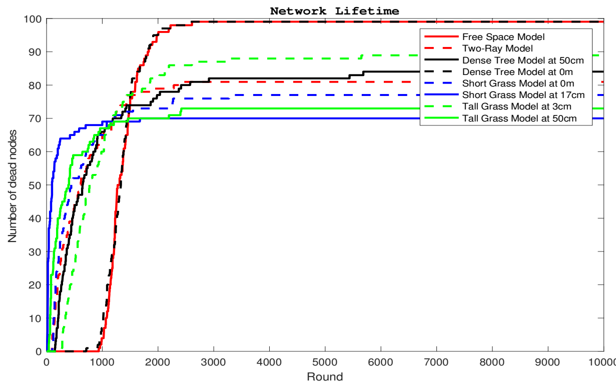

Figure 5. Lifetime of square deployment in rounds for all terrains.

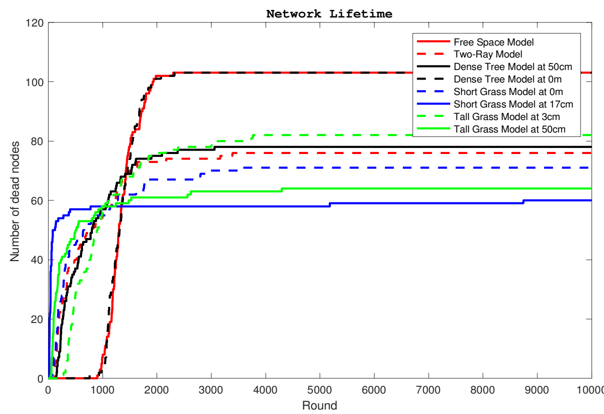

Figure 6. Lifetime of hexagonal deployment in rounds for all terrains.

The results of simulating the propagation models of different environments with different deployments show a significant difference between the theoretical propagation model and the empirical propagation model. Placing nodes on the ground in a dense tree environment yields the longest network lifetime, whereas setting the nodes over the ground (height of seventeen cm) in a short grass environment yields the lowest lifetime. The first node dies in the dense tree environment at 3519 rounds with 62025 total packets sent to the base station. This finding is lower than the results received from the free space model. For short grass with the nodes spaced at a height of 17 cm, the first node dies in the third round with only 31 packets sent to the base station from the entire network. The significant variations in the lifetime of the network are caused by the path loss exponent of each terrain. The dense tree environment has a path loss exponent of 2.81, which is the lowest path loss exponent among all terrains, whereas the short grass environment has the highest path loss exponent of 3.9. The lifetime is stable for all terrains, even if the number of nodes is increased; however, it gradually decreases with the random deployment. Stochastic and deterministic deployments have the highest lifetime with 50 to 100 nodes. Placing the nodes on the ground among a dense tree environment ensures the longest network lifetime, whereas setting the nodes over the ground in a short grass environment produces the lowest lifetime. The number of dead nodes becomes stable with 60 to 80 nodes for most terrains for all deployments. The lifetime is the highest with random deployments compared to other deployment options. All deterministic deployment nodes have a lower lifetime due to the required distance between two nodes to cover all regions of interest. This arbitrary distance causes the data transmission cost to exceed the random deployment.

4.2. Connectivity

The results obtained from the framework are presented in the following figures.

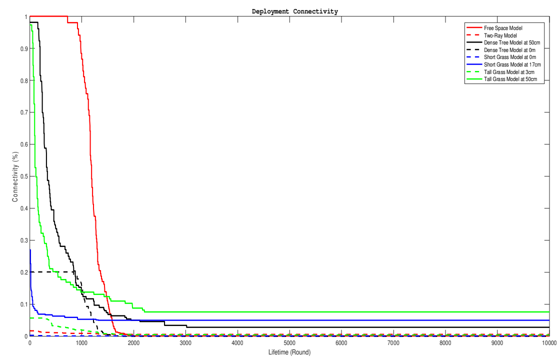

Figure 7. Connectivity of random deployment for all terrains.

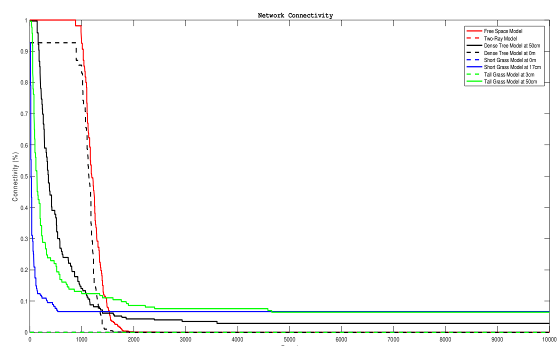

Figure 8. Connectivity of triangular deployment for all terrains.

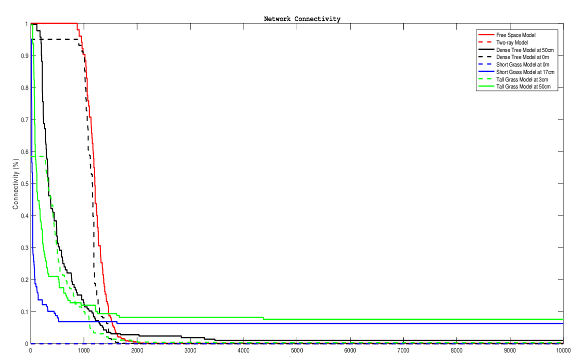

Figure 9. Connectivity of square deployment for all terrains.

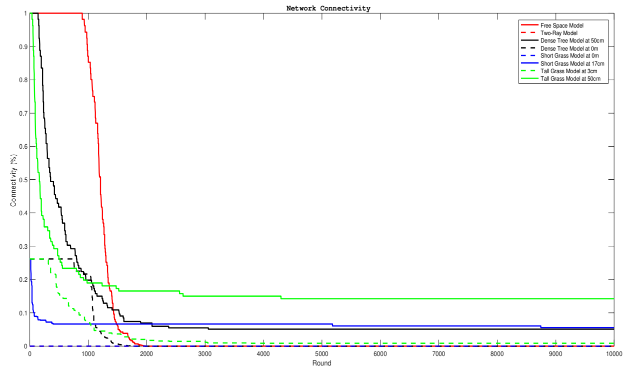

Figure 10. Connectivity of hexagonal deployment for all terrains.

Figures 7-10 represent the connectivity over all terrains with stochastic and deterministic deployments. The theoretical free space model, model of dense tree terrain at 50 cm, and model of tall grass terrain at 50 cm have the highest connectivity, whereas all other terrains have low connectivity for the majority of deployment choices. This finding is attributed to the low median path loss at the reference distance. The dense tree model with a height of zero meters has a high connectivity with square and triangular deployments due to the distance between two nodes, which is enables a high connectivity. For all terrains, the connectivity percentage decreases after few rounds due to the high number of nodes that have died. Square and hexagonal deployments attain a high connectivity level with 50 to 100 nodes. To optimize the connectivity of random deployments, nearly 150 to 200 nodes are needed. The triangular deployment has the lowest cost due to the small number of nodes that are required to obtain a high level of connectivity.

4.3. Coverage

The following figures illustrate the amount of coverage that is provided by each deployment and the change in the coverage percentage over the network lifetime for each terrain.

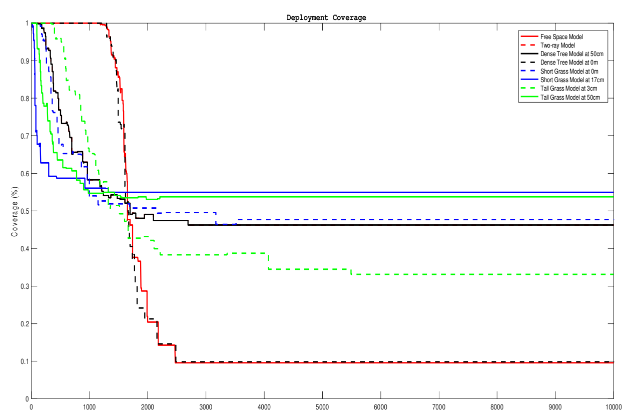

Figure 11. Change in coverage for all terrains with random deployment.

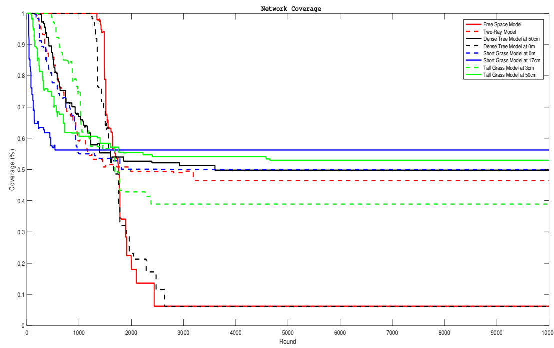

Figure 12. Change in coverage for all terrains with triangular deployment.

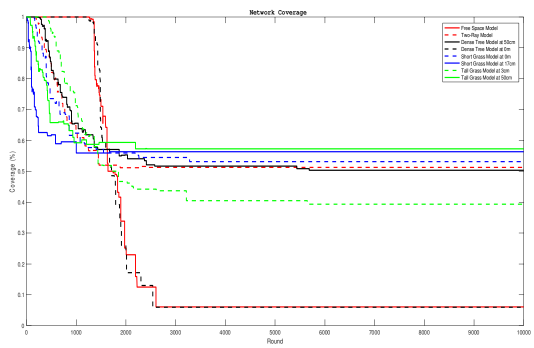

Figure 13. Change in coverage for all terrains with square deployment.

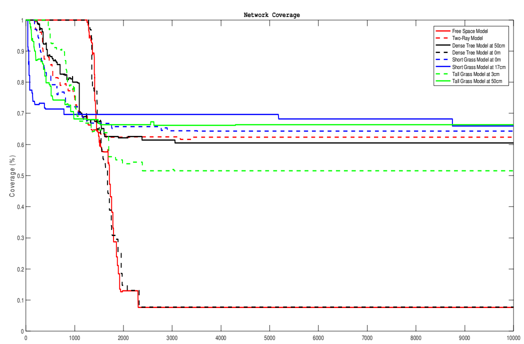

Figure 14. Change in coverage for all terrains with hexagonal deployment.

Figures 11 to 14 illustrate the coverage in the region of interest, which is defined by at least 35 nodes for hexagonal deployment, 52 nodes for triangular deployment, 50 nodes for random deployment, and 56 nodes for square deployment, respectively. They deploy with a variable sensing range for each of the deployments starting from 5 m to 30 m. With a 10- to 15-meter sensing range, the triangular deployment achieves almost full coverage in the region of interest. Square deployment can provide similar coverage with a few additional nodes. For each deployment choice, the region of interest can be covered with a high sensing range: 30 m for random deployment, 25 m for triangular and square deployment, and more than 30 m for hexagonal deployment. Hexagonal deployment utilizes the highest number of nodes, followed by square, triangular, and random deployments. However, random deployment seems inefficient due to its defined number of nodes that are randomly stationed. An analysis of the applied techniques applied shows that the hexagonal technique has the largest number of nodes. However, triangular deployment is the best pattern regarding efficiency within the same region.

4.4. Throughput

The following figures show the final throughput for each type of deployment and terrain and the impact of deployment and terrain variations on the final throughput of the deployed network.

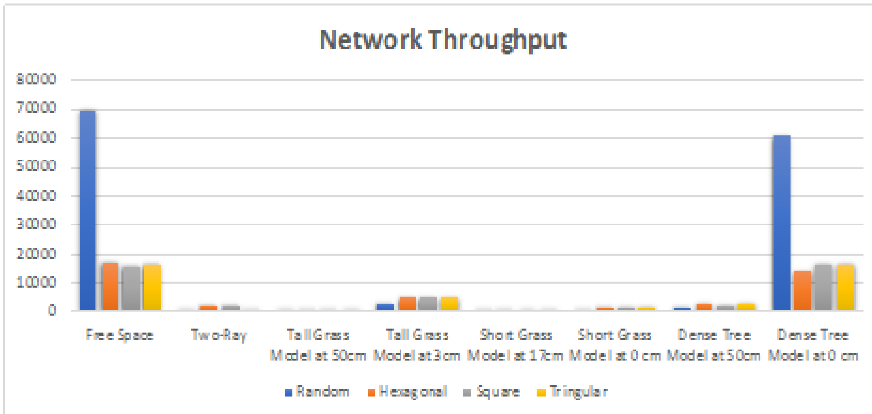

Figure 15. Number of received packets by the base station for each terrain with stochastic and deterministic deployments.

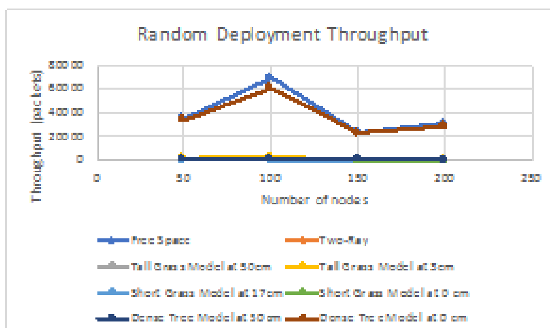

Figure 16. Random deployment throughput with a variable number of nodes for each terrain.

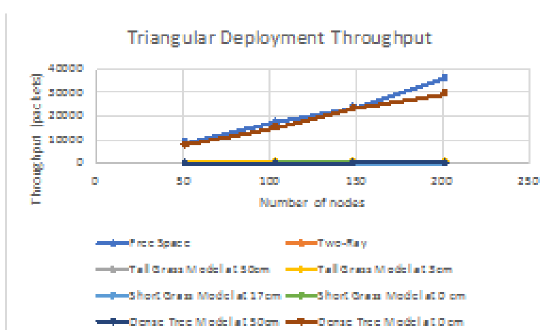

Figure 17. Triangular deployment throughput with a variable number of nodes for each terrain.

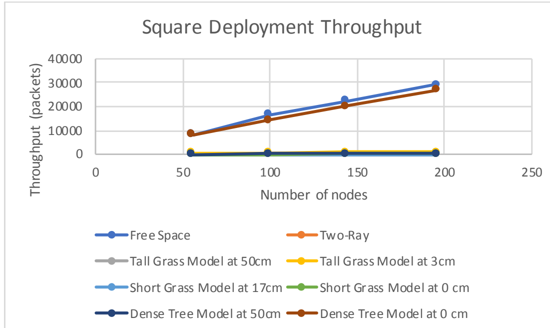

Figure 18. Square deployment throughput with a variable number of nodes for each terrain.

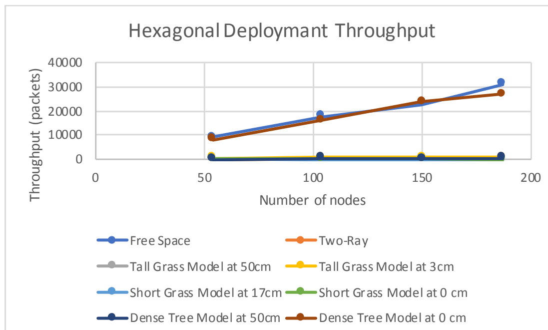

Figure 19. Hexagonal deployment throughput with a variable number of nodes for each terrain.

Figures 15-19 represent the network throughput after ten thousand rounds, which shows the number of packets that has been successfully received by the base station. As illustrated in the figures, the random deployment has the highest throughput compared with other deployments. For all deterministic deployments, the throughput increases by adding nodes and decreases in the random deployment for more than 100 nodes. Most of the terrains produce a throughput that is similar to the throughput of the theoretical two-ray model. However, they have a low throughput compared with the dense tree model with the nodes on the ground, which is similar to the free space model. With the exception of the dense tree model with the node on the ground, the impact of the deployments, either random or deterministic, among these choices is similar.

5. CONCLUSIONS AND FUTURE WORK

This paper presents a realistic deployment framework that investigates WSN performance for several stochastic and deterministic deployments. The study shows that deterministic deployment is not the optimum solution when considering a holistic viewpoint, as shown in the literature review. A trade-off exists among selecting the optimum coverage, connectivity, lifetime, and throughput. This study investigates the impact of empirical propagation models on WSN performance. Table 3 summarizes the deployment options and shows the best choice of deployment option for each number of nodes from 50 nodes to 200 nodes. The empirical propagation model was utilized for dense trees, tall grass, and short grass with different heights to devise an accurate performance analysis that considers the surrounding environment. The findings of this study indicate that theoretical propagation models are not precise in determining WSN performance and the evaluation of WSN performance should include empirical propagation models. The findings of this research will support deployment decision makers due to its focus on the impact of real environments and the deployment choices that can be applied in the pre-deployment stage to predict and optimize the deployment efficiency. Future research will focus on optimizing the simulation framework by incorporating artificial intelligence and prediction methods. Determining the optimum number of nodes to be deployed for each terrain and their locations is an open issue to further investigation. Additional stochastic deployments need to be included and analyzed. In addition, the impact of deployment and terrain needs to be explored with additional routing protocols. The scope of future research should be expanded to determine the performance of multi-terrain environments.

Table 1. Holistic Performance Summary for Stochastic and Deterministic Deployments.

Performance	**Number of nodes**	**Random**	**Square**	**Hexagonal**	**Triangular**
Throughput	50	√			
	100	√			
	150	√			√
	200				√
Lifetime	50	√			
	100	√			
	150	√			√
	200				√
Coverage	50				√
	100				√
	150				√
	200		√		√
Connectivity	50	√			
	100	√			
	150		√		
	200				√

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